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Energy consumption and economic growth in the USA: Evidence from renewable energy

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ABSTRACT

Recent debates about renewable energy consumption manifest two main expectations. Firstly, renewable energy consumption should contribute to economic growth and secondly, it should not cause damage on environment. This study focuses on the first issue by applying Toda–Yamamoto procedure and bootstrap-corrected causality test for the US since empirical literature criticizes the Toda–Yamamoto test which bases on asymptotic distribution. The models consist of real GDP, employment, investment and kinds of renewable energy consumption. Only one causal relationship was found from biomass-waste-derived energy consumption to real GDP. No causal relationship was found between real GDP and all of the other renewable energy kinds—total renewable energy consumption, geothermal energy consumption, hydro-electric energy consumption, biomass energy consumption and biomass-wood-derived energy consumption. That is using of energy from waste cause not only solving the dumping problems but also it contributes to real GDP. For policy purpose, the results of this study suggest that countries should concentrate on energy producing from waste as an alternative energy resource.

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1. Introduction

Sustainable development can be defined as: "development that meets the needs of the present without compromising the ability of future generations to meet their own needs". Many factors can contribute to achieving sustainable development goal. One of the most important factors is the sustainable supply of energy resources [21,8,7]. A secure supply of energy resources is a necessary condition but not sufficient requirement for sustainable development within an economic society. Furthermore, sustainable development needs a sustainable supply of energy resources and an effective and efficient utilization of energy resources. In this context, renewable energy is one of the crucial elements for sustainable development. A number of factors lead to increase attention on renewable energy sources such as the volatility of oil prices, the dependency on foreign energy sources, and the environmental consequences of carbon emissions and government policies that promote renewable energy production [5,1].

Recent debates about renewable energy consumption manifest two main expectations. Firstly, renewable energy consumption should contribute to economic growth and the secondly, it should not cause a damage on environment [10]. This study focuses on first issue. There are four hypotheses about causal nexus between economic growth and energy consumption. According to *the growth hypothesis* energy consumption contributes to economic growth both directly and/or indirectly by complementing to labor

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and capital in the production process. Validity of the growth hypothesis implies that energy conservation policies could reduce real GDP. *The conservation hypothesis* implies that energy conservation policies would not reduce real GDP. Achieving unidirectional Granger-causality from real GDP to energy consumption supports the conservation hypothesis. Interdependent causal nexus between energy consumption and real GDP is suggested by *the feedback hypothesis*. It is supported by the validity of bidirectional Granger-causality between energy consumption and real GDP. Finally, *the neutrality hypothesis* proposes that energy consumption serves a relatively minor role in the determination of real GDP while energy conservation policies would not reduce real GDP. The absence of Granger-causality between energy consumption and real GDP supports the neutrality hypothesis.

Ozturk [17] reviews the literature about energy consumption-economic growth nexus. Empirical evidence about causal nexus between energy consumption and real GDP are mixed (while Ozturk and Acaravci [18] found no causal relation, Kum et al. [14] concluded that there is Granger causality is from energy consumption to growth for Italy and two sided causality is for France, Germany and United States).

Furthermore very few studies investigate the relationship between renewable energy consumption and real GDP. Table 1 summarizes empirical literature about renewable energy consumption-economic growth nexus.

Only Payne [19] and Bowden and Payne [5] use Toda–Yamamoto [26] causality test. But the Toda–Yamamoto test which bases upon the lag-augmented VAR model has assumption of the normality of the error term. Hacker and Hatemi [11] indicate that if the error term of the model is characterized by non-normality, asymptotic distribution can be poor approximation. In this case findings of Toda–Yamamoto test are invalid.

The contribution of our empirical study is threefold. First this study uses a multivariate causality test by including employment and investment variables into the model between renewable energy consumption and real GDP since the omission of relevant variables leads to econometric problems. Second, this study employs bootstrap-corrected causality technique suggested by Hacker and Hatemi [11] to avoid unclear results due to the assumption of normality and the third one is to pick the true lag order by combining Schwarz [25] Bayesian information criterion and the Hannan and Quinn [12] information criterion as suggested by Hatemi [13].

The rest of the paper is organized as follows: the next section describes the data, methodology and the results from empirical analysis are presented in third section. Section 4 presents conclusion and policy implications of the paper.

2. Data

Employment, real gross fixed capital formation and real GDP variables are taken from OECD National Accounts data that is attained from source OECD data base and time series of renewable energy consumption variables are obtained from the US Energy Information Administration as billion Btu. Time span of the renewable energy consumption variables are as follows: 1949–2010 for total renewable energy consumption, biomass energy consumption, hydropower energy consumption and biomass-wood-derived energy consumption, 1960–2010 for geothermal energy consumption and 1970–2010 for biomass-waste-derived energy consumption.

3. Methodology and results

The analyses consist of four stages. In the first stage, to ensure robustness for the common components of the variables, we use several unit root tests, including the Phillips and Perron [20] (PP) test and the Kwiatkowski et al. [15] (KPPS) test. Table 2 reports the results of unit root tests.

The next step is to pick optimal lag order. Two of the most successful criteria according to the simulation results presented in the literature are Schwarz [25] Bayesian information criterion (SBC) and the Hannan and Quinn [12] information criterion (HQC). Schwarz criterion can be represented as following:

$$\mathrm{SBC} = ln(det\tilde{\Omega}_j) + j\frac{n^2 ln\,T}{T}, \quad j = 0,\ldots,K$$

where $\tilde{\Omega}_j$ is the maximum likelihood estimate of the variance-covariance matrix $\grave{U}$ when the lag order used in estimation is j. T is the sample size. The goal is to estimate k_l by the j that minimizes the above criterion. Hannan-Quin [12] introduces an alternative information criterion.

$$\mathrm{HQC} = ln(det\tilde{\Omega}_j) + j\frac{2n^2 ln(ln\,T)}{T}, \quad j = 0,\ldots,K$$

The earlier studies illustrate that each of these two different criteria can perform better than the other depending on the properties of the true VAR model. But the true VAR model is not known in empirical analysis. If SBC and HQC pick two different lag orders it is difficult to know which criterion one should rely on. In this situation Hatemi-J [13] suggests combining these two criteria to obtain the following information criterion (HJC):

$$\mathrm{HJC} = ln(det\tilde{\Omega}_j) + j\left(\frac{n^2 ln\,T + 2n^2 ln(ln\,T)}{2T}\right) \quad j = 0,\ldots,K$$

Table 1
Literature review: renewable energy consumption and economic growth.

Study	Methodology	Period	Subject	Relationship
Sari and Soytas [23]	Variance decomposition	1969–1999	Turkey	REC increases GDP
Ewing et al. [9]	Variance decomposition	2000:1–2005:6	US	REC increases IP
Sari et al. [24]	ARDL	2000:1–2005:6	US	IP → REC
Sadorsky [22]	Panel Cointegration	1994–2003	18 emerging countries	GDP → REC
Apergis and Payne [1]	Panel Cointegration	1985–2005	20 OECD countries	GDP ↔ REC
Apergis and Payne [2]	Panel Cointegration	1992–2007	13 countries within Eurasia	GDP ↔ REC
Payne [19]	Toda–Yamamoto	1949–2006	US	GDP ≠ REC
Bowden and Payne [5]	Toda–Yamamoto	1949–2006	US (sectoral level)	GDP ↔ REC
Menegaki [16]	Panel random effect model	1997–2007	27 European Countries	GDP ≠ REC
Apergis and Payne [3]	panel error correction model	1980–2006	6 Central American countries	GDP ↔ REC
Apergis and Payne [4]	panel error correction model	1990–2007	80 countries	GDP ↔ REC

Note: Abbreviations are defined as follows: REC = renewable energy consumption, GDP = real gross domestic product, IP = industrial production. EC → GDP means that the causality runs from energy consumption to growth. GDP → EC means that the causality runs from growth to energy consumption. EC ↔ GDP means that bidirectional causality exists between energy consumption and growth. EC ≠ GDP means that no causality exists between energy consumption and growth.

Table 2
Results of unit root tests.

Variable	Phillips-Perron			KPSS	
	None	Intercept	Intercept and trend	Intercept	Intercept and trend
Real GDP	I(1)	I(0)	I(1)	I(1)	I(1)
Gross fixed capital formation	I(1)	I(1)	I(1)	I(1)	I(0)
Employment	I(1)	I(1)	I(1)	I(1)	I(1)
Total renewable energy consumption	I(1)	I(1)	I(1)	I(1)	I(1)
Total biomass consumption	I(1)	I(1)	I(1)	I(1)	I(0)
Wood and wood-derived fuels consumption	I(1)	I(1)	I(1)	I(1)	I(1)
Waste-derived fuel consumption	I(1)	I(1)	I(1)	I(1)	I(1)
Hydro-electric consumption	I(1)	I(1)	I(1)	I(1)	I(1)
Geothermal electricity consumption	I(1)	I(1)	I(1)	I(1)	I(0)

Note: According to our results maximum integration order of the common components of the variables are one, I(1).

Using Monte Carlo simulation Hatemi-J [13] illustrates that HJC choose the optimal lag order both in stable and unstable VAR models. Therefore Hatemi-J Criteria, displayed in Table 2, is employed to pick true lag order.

Third step of the analysis is to run causality test. Causal relationships between growth and energy are frequently analyzed using Granger causality test. Granger (1969) runs a regression model which relies on asymptotic distribution theory. But, using Monte Carlo simulations Granger and Newbold (1974) find that if the variables are non-stationary, the regression analysis based on the asymptotic distribution theory does not work well. So the found results can be spurious. Sims et al. (1990) depicted that when the variables are non-stationary the vector autoregressive (VAR) model cannot be used in level form even if the variables are co-integrated. In this case, based on the lag augmented VAR model, Toda and Yamamoto [26] propose a Wald test statistic that asymptotically has a chi-square distribution irrespective of the order of integration or cointegration properties of the variables in the model. Toda–Yamamoto augmented the VAR(p+d) model can be described in the following a compact way ([11]):

$$K = FZ + \psi \tag{1}$$

where

$K = (x_1, \ldots, x_T)(n \times T)$matrix,
$F = (\nu, A_1, \ldots, A_p, \ldots, A_{p+d})(n \times (1+n(p+d)))$matrix,

$$Z_t = \begin{bmatrix} 1 \\ x_t \\ x_{t-1} \\ \cdot \\ \cdot \\ \cdot \\ x_{t-p-d+1} \end{bmatrix} ((1+n(p+d)) \times 1)\text{matrix, for } t = 1,\ldots,T, \text{ matrix,}$$

$Z = (Z_0, \cdots, Z_{T-1})((1+n(p+d)) \times T)$matrix,
$\psi = (\varepsilon_1, \cdots, \varepsilon_T)(n \times T)$matrix,

Toda and Yamamoto [26] introduce the following modified Wald (MWALD) test statistic for testing the null hypothesis of non-Granger causality

$$\text{MWALD} = (Y\phi)'[Y((Z'Z)^{-1} \otimes V_U)Y']^{-1}(Y\phi) \sim \chi^2_P \tag{2}$$

where $\otimes$ = the Kronecker product, $Y = ap \times n(1+n(p+d))$, V_U = the estimated varience–covariance matrix of residuals in Eq. (1), ϕ = vec (F), where vec represents the column stacking operator.

The MWALD test statistic is asymptotically χ^2 distributed, conditional on the assumption that the error terms are normally distributed, with the number of degrees of freedom equal to the number of restrictions to be tested. According to Toda and Yamamoto [26], their function Eq. (2) guarantees the use of asymptotical distribution theory. However, using Monte Carlo simulations Hacker and Hatemi-J [11] showed that the MWALD test statistic over rejects the null hypothesis, especially if the error term is characterized by autoregressive conditional heteroscedasticity (ARCH) and non-normality. Furthermore, Hacker and Hatemi-J urged that the asymptotic distribution can be a poor approximation, especially for the small samples that are common in empirical studies.

Hacker and Hatemi-J [11] found that the bootstrapped empirical size for the modified Wald test is close to the correct size in the different cases when the extra lags are greater than or equal to the integration order of both variables, and it is generally closer to the correct size than the asymptotic distribution empirical size. The leveraged bootstrap causality test ensures that the presence of heteroscedasticity does not affect the accuracy of estimated results.

To perform the bootstrap simulations, following steps are traced as suggested by Hacker and Hatemi-J [11]

1. Firstly regression Eq. (1) is estimated with the null hypothesis of no Granger causality.
2. After simulated the bootstrapped residuals via resampling with replacement, for each bootstrap simulation it is generated the simulated data, K^*.

$$K^* = \hat{F}Z + \psi^* \tag{3}$$

3. Calculate the parameter vector by using K^* and denote it F^*.
4. Calculate the WALD test statistics presented in Eq. (2) by using the bootstrapped data.
5. Repeat step 2–4 N times and rank the estimated values of the WALD* test in order to produce its bootstrapped distribution.
6. Take the (á)th upper quantile of the distribution of bootstrapped (WALD*) statistics, to obtain the á-level "bootstrap critical values" (c^*_α).
7. The final step in the procedure is to calculate the WALD statistic using the original data. The null hypothesis is rejected at the á level of significance if WALD $> c^*_\alpha$.

The bootstrap residuals ($\emptyset^*$) are based on T random draws with replacement from the regression's modified residuals, each with equal probability of $1/T$. The mean of the resulting set of drawn modified residuals is subtracted from each of the modified residuals in that set. The modified residuals are the regression's raw residuals modified to have constant variance, through the use of leverages. In order to calculate the bootstrap critical values, the bootstrap simulation is run 100,000 times and calculated the MWALD test statistic each time. In this way, it is able to produce the empirical distribution for the MWALD test statistic. Table 3

For the aim of comparison, both Toda–Yamamoto (TY) procedure and bootstrap-corrected causality test were employed. To

Table 3
Selection of lag length.

Models	SBC	HQC	HJC
Model 1:Real GDP=Employment+Investment+Total REC	[1] (−17.6647)	[2] (−18.3052)	[2] (−17.9066)
Model 2:Real GDP=Employment+Investment+Biomass Total EC	[2] (−18.0247)	[2] (−18.8220)	[2] (−18.4233)
Model 3:Real GDP=Employment+Investment+Hydropower EC	[1] (−16.6757)	[2] (−17.3138)	[2] (−16.9152)
Model 4:Real GDP=Employment+Investment+Biomass wood-derived EC	[2] (−18.4142)	[2] (−19.2114)	[2] (−18.8128)
Model 5:Real GDP=Employment+Investment+Biomass-waste-derived EC	[2] (−14.8194)	[6] (−16.5588)	[2] (−15.3432)
Model 6:Real GDP=Employment+Investment+Geothermal EC	[2] (−15.6311)	[2] (−16.5377)	[2] (−16.0844)

Note: Abbreviations are defined as follows: SBC=Schwarz Bayesian information criteria, HQC=Hannan-Quinn information criteria, HJC=Hatemi-J information criteria, REC=Renewable energy consumption and EC=Energy consumption. The numbers in brackets are the optimal lag lengths and min test statistics are in the parenthesis.

Table 4
Causality test results based on HJC.

	H0: REC does not Granger cause GDP					**H0: GDP does not Granger cause REC**				
	MWALD	TY Prob	%1 CV	%5 CV	%10 CV	MWALD	TY Prob	%1 CV	%5 CV	%10 CV
Model 1	0.069	0.9663	10.505	6.590	4.974	2.288	0.3186	10.727	6.764	5.087
Model 2	2.226	0.3286	11.078	6.833	5.162	1.602	0.4490	10.847	6.764	5.108
Model 3	0.966	0.6169	10.272	6.447	4.915	1.261	0.5323	10.754	6.758	5.090
Model 4	1.637	0.4412	10.610	6.623	4.996	1.684	0.4308	10.965	6.839	5.181
Model 5	**12.422**[a]	**0.0020**[a]	11.681	6.969	5.160	4.482	0.1063	11.872	7.003	5.186
Model 6	1.228	0.5411	11.064	6.871	5.148	0.332	0.8468	11.603	6.994	5.255

[a] Rejection of null hypothesis at 1% significance level. TY prob is estimated probability value by Toda–Yamamoto procedure for the MWALD stat. REC=Renewable energy consumption. For definitions of the models see Table 3.

Table 5
Causality test results based on HQC and SBC.

	H0: REC does not Granger cause GDP					**H0: GDP does not Granger cause REC**				
	MWALD	TY Prob	%1 CV	%5 CV	%10 CV	MWALD	TY Prob	%1 CV	%5 CV	%10 CV
Model 1	0.0018	0.9665	7.247	4.065	2.819	0.0053	0.9420	7.378	4.174	2.916
Model 3	0.1796	0.6717	7.209	4.062	2.838	0.5566	0.4556	7.408	4.199	2.918
Model 5	3.5207	0.7412	72.685	34.049	23.291	2.3583	0.8840	77.538	35.551	24.257

TY prob is estimated probability value by Toda–Yamamoto procedure for the MWALD stat. REC=Renewable energy consumption. For definitions of the models see Table 3.

estimate bootstrap-corrected causality test the code written by Hacker and Hatemi-J [11] was used. Table 4 illustrates the MWALD stats and critical values.

According to Table 4 TY procedure and bootstrap-corrected causality test reach same results. But statistical significance levels of MWALD test are changed. For example while according to result of TY procedure, null hypothesis of no Granger causality from real GDP to biomass-waste-derived energy consumption (Model 5) is not rejected at 10% significance level by a small margin, bootstrap-corrected causality test strictly rejects the null hypothesis at 10% significance level. So there is very small bias due to the assumption of normality and results of Toda and Yamamoto procedure are valid.

Both Toda–Yamamoto procedure and bootstrap-corrected causality test find just the causal relationship from biomass-waste-derived energy consumption to real GDP. This finding supports the growth hypothesis. No causal relationship was found between all of the other renewable energy kinds and real GDP. All of the findings, except for biomass-waste-derived energy consumption, support the neutrality hypothesis.

In the last step, to see whether selection of lag length is important for the achieving results, different lag length selected by HQC and SBC (see Table 3) are used to estimate the causal nexus between energy consumption and economic growth. Table 6 reports the causality tests results based on HQC.

According to Table 5 using SBC for lag selection changes only significance level of MWALD test for Model 1 and Model 3. While choice of HJC leads unidirectional causal nexus from biomass-waste-derived energy consumption to real GDP, HQC based estimation cause no causal relationship for Model 5. Since HJC choose optimal lag order for stable and unstable VAR model, one can conclude that HJC leads to correction for selection of lag length.

4. Conclusion

Recent debates about relationship between renewable energy consumption and economic growth manifest two main expectations. Firstly, renewable energy consumption should contribute to economic growth and secondly, it should not cause damage on environment. This study focuses on the first issue by applying bootstrap-corrected causality test for the US since empirical literature criticizes the Toda–Yamamoto test which bases on asymptotic distribution. This study finds that there is very small bias due to the assumption of normality and results of Toda and Yamamoto procedure are valid. But selection of lag length is important. Since HJC choose optimal lag order for stable and unstable VAR model, HJC leads to correction for selection of lag length.

According to causality test results only one causal relationship was found from biomass-waste-derived energy consumption to real GDP. No causal relationship was found between all of the other renewable energy kinds and real GDP. These findings are interesting since biomass-waste-derived energy consumption has a low percentage (6%) of total renewable energy consumption.

Many developed countries are trying to dump their garbage on the lands of lesser developed countries. However dumping garbage on other places spreads pollutions and diseases instead of solving the problem. In fact it is more dangerous to dump garbage in the less developed countries since there are neither technologies available to process it nor enough awareness. Even creating landfills wastes precious resources. Lastly our findings indicate that there is a causal relationship from waste-derived energy to real GDP. Using of energy from waste cause not only to resolve the dumping problems but also it contributes to real GDP. The countries that are using other energy resources do not take advantage from using waste-derived energy. For policy purpose, the results of this study suggest that countries should concentrate on energy producing from waste as an alternative energy resource.

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